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Non-Linear Multiple Field Interactions Neural Document Ranking

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ABSTRACT

Ranking tasks are usually based on the text of the main body of the page and the actions (clicks) of users on the page. There are other elements that could be leveraged to better contextualise the ranking experience (e.g. text in other fields, query made by the user, images, etc). We present one of the first in-depth analyses of field interaction for multiple field ranking in two separate datasets. While some works have taken advantage of full document structure, some aspects remain unexplored. In this work we build on previous analyses to show how query-field interactions, non-linear field interactions, and the architecture of the underlying neural model affect performance.

CCS CONCEPTS

• **Applied computing** → **Document management and text processing**; • **Information systems** → **Learning to rank**.

KEYWORDS

recipes, neural networks, field interactions, query-field, first-order, document ranking

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1 INTRODUCTION

Modern online documents consists of a number of fields, such as title, body, the anchor text from incoming hyperlinks, or the query text for which the document has been previously viewed.

However, recent efforts have suggested that field dependencies are not critical for some search applications[10, 17].

This is a counter-intuitive result as one may think multiple fields associated with each document may contain complementary information; this, in turn, can improve the performance of the ranking task.

This intuition was exploited by traditional information retrieval techniques where field interactions are explicitly considered and

deemed to be important [16]. A number of techniques has been explored to represent these interactions and their impact in information retrieval [6, 7, 14, 18].

Until recently, deep neural ranking models (NRMs) tended to consider a single source of document description, such as document title [4] or body text [3]. Interactions between fields have recently started to be considered in NRMs.

Field relevance modelling is usually conceived in two different ways: 1) from fields represented independently and then combined to create a weighted mode [8, 20] or 2) directly from the entire document and using a relevance model to score fields [8].

While [20] explicitly learn query-field interactions, no prior works have not explicitly explored the nature of field-to-field interactions to better understand their inter-relations. Simple combinations of relevance on each field [8] or field representation concatenations [20] have been used. Like in attention models for natural language processing, it may be that some interactions between fields are non linear in nature. The order of field-to-field non linearities and their impact on ranking performance is unexplored.

We evaluate our models in the context of web search, using the queries sampled from the Cookpad's¹ search logs. We study multiple field combinations to understand if more complex non-linear combinations can have an impact on retrieval performance.

In order to assess the robustness of our findings, this work also explores the impact of the architectural model employed for the information retrieval task.

In this work, we study the following research hypotheses:

- **H1** Non-linearities in field-to-field interactions have an impact in ranking performance.
- **H2** Specific field-to-field interactions affect performance (beyond query-field interactions).
- **H3** The importance of field interactions are dependent on the neural architecture employed for the analysis.

Our experiments validate all these hypotheses, and investigate the effectiveness of our overall exploration of field interactions.

2 RELATED WORK

2.1 Retrieval with Multiple Fields

Classic works already relayed on the usage of information from multiple fields in a document [15]. Robertson et al. [16] extended the original BM25 model to create the BM25F model, which combines frequency information across fields on a per-term basis and then computes a retrieval score using a balanced approach.

Other approaches built on this idea without resorting to a linear combination of per-field scores: like, for instance, Bayesian

¹<http://www.cookpad.com>

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networks [14], LambdaBM25 [18] (based on LambdaRank [2]), language modeling framework [12], probabilistic models [6], or feed-back weighted field relevance [7].

2.2 Neural Networks for Ranking

Mitra et al. have shown that no significant loss is observed in models that incorporate the query term independence assumption (order of words does not matter and relevance is only measured if a word is in the query) in web search [10].

State-of-the-art BERT-based models are mediocre in product search [17]. Together, these works suggest that capturing inter-term dependencies is not critical in some search applications, even though it is a central concern in question answering.

While there are many works focusing on the application of neural models to information retrieval [9], but most of them treat each document as a single instance of text (i.e., single field).

However, documents often include information in a semi-structured format and multiple fields. A few studies have discussed how to use evidence from structure to improve the performance of information retrieval systems.

Wilkinson proposed several heuristic methods of combining section-level and document-level evidence, such as taking the maximum section score or taking a weighted sum of section scores [19].

NRM-F, proposed by Zamani et al. [20], is the only paper that discusses how neural models can deal with multiple document fields from an architectural perspective. The authors say that it is better for the ranker to score the whole document jointly, rather than generate a per-field score and aggregate.

NRM-F formulates the document representation learning function Φ_D as follows:

$$\Phi_D(F_d) = \Lambda_D(\Phi_{F_1}(F_1), \Phi_{F_2}(F_2), \dots, \Phi_{F_k}(F_k))$$

where Φ_{F_i} denotes the mapping function for the field F_i and Λ_D aggregates representations learned for all the fields. Λ_D simply concatenates the input vectors to be served in the matching function. Then, a stack of fully-connected layers outputs the final retrieval score.

In NRM-F, both query text and text fields are represented using a character n -gram hashing vector as in [4]. Then, a convolution layer is employed to capture the dependency between terms.

This model explicitly learns query-field interactions, but it does not distinctly consider field-to-field interactions. Importantly, the effect of non-linear interactions between fields is also not taken into account. NRM-F also exclusively focuses on query-field interactions (scoring the whole document jointly), but there may be other important field interactions to consider.

[8] also focus on query-to-field interactions and assume there are just linear relationships between relevance models induced from each fields.

When designing a ranking model, several architecture decisions need to be made, such as representation-based vs. interaction-based, which field interactions to learn, how to aggregate scores, etc. These fundamental design decisions were not clearly justified in prior efforts and the impact of the chosen architectural model on ranking remains unclear.

There are several potential models that have been used to assess the effectiveness of field-interactions. Factorization Machine (FM)

| | |
|---------------------------|-----------|
| #queries | 2,733,549 |
| #unique queries | 94,993 |
| #unique presented recipes | 301,078 |

Table 1: Basic Statistics of the Cookpad dataset

| Field | Type | Example |
|-------------|------------|---|
| recipe_id | Integer | 1 |
| title | String | Honey garlic chicken thighs |
| description | String | This recipe has always been my favorite |
| ingredients | String set | chicken, salt, crushed red chilli, ... |
| country | String | GB |

Table 2: The schema of recipe data

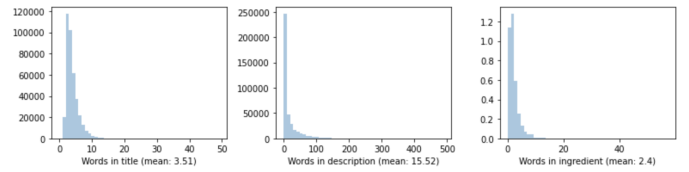


Figure 1: Number of words in text fields in the Cookpad data

is a widely used supervised learning approach by effectively modeling of feature interactions. In FM, unseen feature interactions can be learned from other pairs. Field-weighted Factorization Machine (FwFM) are state-of-the-art among the shallow models for click-through-rate prediction [13].

3 METHODOLOGY

3.1 Datasets

3.1.1 MS MARCO Dataset. Microsoft has released a large web search dataset called MS MARCO². The documents consist of multiple fields.

3.1.2 Recipe Search Dataset. Cookpad³ is the number one Japanese online recipe community platform. Users can publish and search for recipes on the platform. The size of the dataset is shown in Table 1. The dataset consists of two subsets: master recipe data and search logs.

Recipes are structured data as shown in Table 2. The description is a free text field; some recipes have a surprisingly long description while there are recipes with no description. The ingredients are an unsorted set of entities.

Figure 1 shows the distribution of the number of words in each field; text fields are generally short in length, making it difficult to capture text significance using term frequency-based methods.

The second subset of data is search logs: event log created when a user clicks a recipe in the search results. The attributes of each event are listed in Table 3. *fetch_recipe_id* indicates what recipes were retrieved against the query and *position* shows the clicked recipe position in the list.

²MS MARCO <https://microsoft.github.io/msmarco/>

³Cookpad <http://www.cookpad.com>

| Field | Type | Example |
|--------------------|---------|-------------|
| session_id | Integer | 1 |
| query | String | hot dessert |
| page | Integer | 1 |
| recipe_id | Integer | 1 |
| position | Integer | 1 |
| fetches_recipe_ids | String | 1,2,3,4,5,6 |
| total_hits | Integer | 256 |

Table 3: The schema of search log in Cookpad

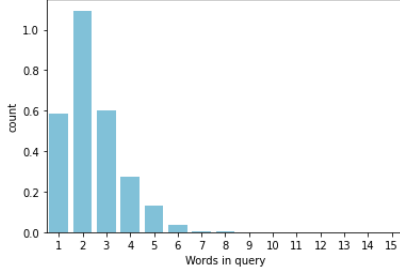


Figure 2: The number of words per query in the Cookpad data

Figure 2 shows the distribution of words in a query. Most queries contain no more than three words.

3.2 Data Processing and Modeling

We selected five fields: query, title, description, ingredients, and country for training. The text embedding is shared across text fields. This data is concatenated with search logs.

Search logs are aggregated by session ID and query, and the result list is trimmed at the clicked position. Labels are then assigned by referring to the position.

We employ pairwise cross-entropy loss.

Regarding the text representation, we obtain fix-sized vectors under the assumption that terms are almost independent. In this type of application, it is not uncommon to assume term independence. Amazon’s experiment showed that taking the average of term vectors performed similar or slightly better than recurrent units with significantly less training time [11]. The countries are treated as a category and embedded into a latent space.

In order to tests if field interactions affect ranking performance in an architecture-dependent manner, we focus on two architectural models: NRM-F [11] and FwFM [13] to examine how the choice of architecture affects effectiveness. The table summarises the differences between those two models.

| | NRM-F | FwFM |
|----------------------------|------------------|-------------|
| First-order features | Not used | Used |
| Interaction selection | Query-field | All |
| Interaction representation | Hadamard product | Dot product |
| Interaction aggregation | Concatenation | Summation |

Table 4: A Comparison of Different Architectures

| Model | NDCG@20 |
|-------------------------------|---------------|
| No interaction learning | 0.6376 |
| Implicit interaction learning | 0.6429 |
| Explicit interaction learning | 0.6483 |

Table 5: Performance comparison of interaction learning

| Pair | p-value |
|---|---------|
| No interaction - Implicit interaction | 0.619 |
| No interaction - Explicit interaction | 0.159 |
| Implicit interaction - Explicit interaction | 0.616 |

Table 6: P-values of Tukey’s test on pairs

We employ Normalised Discounted Cumulative Gain (NDCG) to evaluate models, with a cut-off of 20 ⁴.

The entire dataset is divided into 10 sets by timestamp to obtain a sufficient number of individual datasets to evaluate the statistical significance of the obtained results. Each dataset is further divided by timestamp, with the first 75% used for training and the remaining 25% for validation.

4 EXPERIMENTS

All the experiments presented in this section are available for reproducibility⁵.

4.1 Impact of Field Interactions

First, we determine whether field interactions have any effect in ranking for our datasets. In order to accomplish this we use:

- **A representation-based model (No feature interaction)**
As a no interaction learning model, we employ a simple representation-based model that consists of two component: query encoder and recipe encoder. Both encoders transform entities into vectors and their cosine similarity is computed at the last layer.
- **An implicit interaction-based model:** The naive interaction-based model simply concatenates all features at the first layer, then the output is fed to several fully-connected layers.
- **An NRM-F-based model):** This model is based on NRM-F, but the text representation was simplified in accordance with the dataset as mentioned above.

Table 5 shows that the interaction-based models outperformed the representation-based model in average performance. Table 6 shows that no statistical significance is observed when performing Tukey’s multiple comparison test to determine if there are statistically differences between those models.

Figure 3 is the boxplot showing the performance of each model. The performance of the representation-based model fluctuates.

⁴this is the number of recipes served per page at Cookpad

⁵<https://github.com/rejasupotaro/master-thesis>

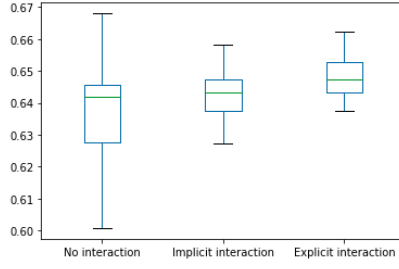


Figure 3: Boxplot showing NDCG scores on whether feature interactions have an impact on our dataset

| Model | NDCG@20 |
|--|---------------|
| NRM-F-based model (query-field interactions) | 0.6483 |
| NRM-F-based model (all interactions) | 0.6403 |
| FM-based model (query-field interactions) | 0.6674 |
| FM-based model (all interactions) | 0.6616 |

Table 7: Performance comparison of models with different interactions

4.2 Query-to-field vs Field-to-field Interactions

Query-field interactions are considered to be important in document ranking, whereas recommendation models do not distinguish between context and item features.

Inspired by recommendation models, which do not usually distinguish between a query and item features, we gauge the effects of adding all field interactions vs focusing on query-field interactions only.

The purpose of this experiment is to investigate whether limiting interactions to just query-field helps to improve performance. To do so, we train two models with different feature interactions:

- **NRM-F (query-field)**: Consider query-field interactions (as the original implementation).
- **NRM-F (all)**: Consider all feature interactions without distinguishing between query and fields.
- **FwFM (all)**: Consider all feature interactions without distinguishing between query and fields (as the original implementation).
- **FwFM (query-field)**: Consider query-field interactions.

Table 7 shows the performance of the above mentioned models. Interestingly, the models that learned query-field interactions outperformed models trained using all interactions in both NRM-F and FwFM. Table 8 shows these differences are statistically significant.

The experiment also has shown that recommendation models could be used for ranking tasks as it is since FwFM outperformed the simplified NRM-F. Besides, we can further improve performance by incorporating the properties of information retrieval into recommendation models.

| Pair | p-value |
|-----------------------------------|---------|
| NRM-F (query-field) - NRM-F (all) | 0.0031 |
| FwFM (query-field) - FwFM (all) | 0.001 |

Table 8: P-values of paired t-tests on each method

| Model | NDCG@20 |
|--------------------|--------------|
| FwFM (all) | 0.662 |
| FwFM (query-field) | 0.667 |
| FwFM (selected) | 0.665 |

Table 9: Performance comparison of models with different interactions

4.3 Importance of Interactions beyond Query-Fields

Subsection 4.2 suggests some naturally leads to wondering whether other field interactions beyond query-field interactions can be identified.

In this set of experiments, we employed the FwFM model, trained using first- and second-order interactions (5 features + 10 feature interactions in total). FMs compute the scores for each field independently and sum them up to produce the final score. We trained the model regularly and extracted the individual feature scores on validation data as shown in the following code snippet.

```
class FwFM(BaseModel):
    def build(self):
        ...
        x = tf.concat([first_order_features, feature_interactions], axis=1)
        # It is individually computed scores.
        scores = tf.keras.Model(inputs=inputs, outputs=x)
        # Sum up the computed scores, which will be the final score.
        x = tf.keras.backend.sum(x, axis=1, keepdims=True)
        output = layers.Activation('sigmoid', name='label')(x)
        final_score = tf.keras.Model(inputs=inputs, outputs=output, name='final_score')
        # `scores` model is used to extract individual
        # scores.
        return final_score, scores
```

Features are sorted by correlation to the label building on the assumption that the correlation should be a proxy indicator for field importance since the sum of individual scores will be the final score. Then, we compare the performance of these three models.

Figure 4 shows the distributions of the activation of fields. The shape of the distribution of query-title is different to that of other fields. Clicked and not clicked distributions coincide: their correlation to the label is zero (see Figure 5).

These results suggest that the model cannot guess which recipe is more likely to be engaged with just by looking at a query. Also, correlation seems to be associated to the importance of the features.

However, table 9 shows the performance of the FwFMs with different features: the model with selected features did not outperform the model with query-field interactions.

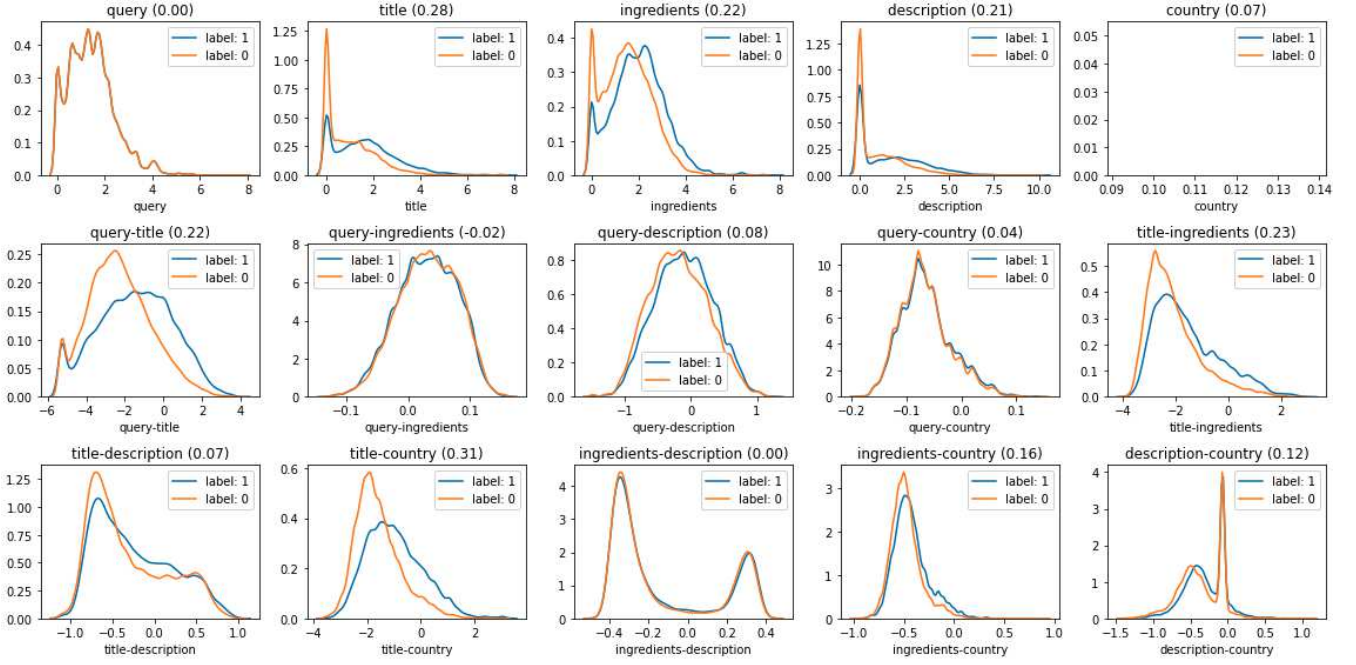


Figure 4: Distribution of outputs of the interaction layer. The label represents 1: clicked and 0: not clicked. The x-axis shows the actual value, and the y-axis is the probability density. The numbers in parentheses indicate the correlation with the label.

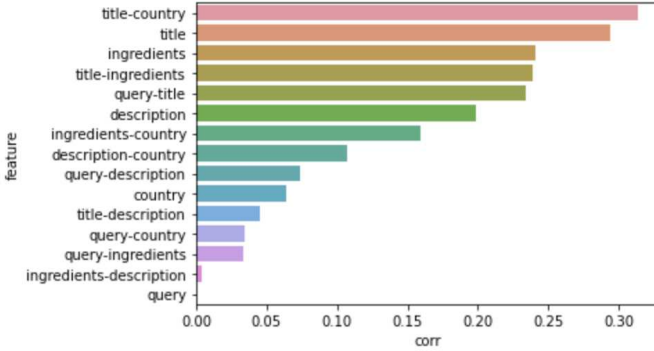


Figure 5: The correlation to the label of each feature.

4.4 Non-Linear Field Interactions

The original implementation of NRM-F does not use first-order field interactions. In this section, we explore the impact of first-order field interactions in performance. For this set of experiments, we use the following fields: query, title, description, ingredient, and country. We define this non-linear, second-order interactions to use vary by model as follows:

- **NRM-F (2nd)**: Use second-order query-field interactions only (as the original implementation).
- **NRM-F (1st + 2nd)**: Use first-order features along with second-order query-field interactions.
- **FwFM (1st + 2nd)**: Use first- and second-order interactions (as the original implementation).

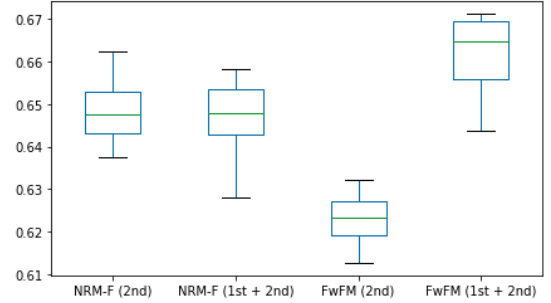


Figure 6: Boxplot showing NDCG scores

| Pair | p-value |
|---------------------------------|---------|
| NRM-F (2nd) - NRM-F (1st + 2nd) | 0.526 |
| FwFM (2nd) - FwFM (1st + 2nd) | 0.0 |

Table 10: P-values of paired t-tests on each method

- **FwFM (2nd)**: Use second-order interactions only.

Figure 6 shows the performance of the models above. It can be seen that there is no difference between NRM-F (2nd) and NRM-F (1st + 2nd) while FwFM (1st + 2nd) significantly outperformed FwFM (2nd) (Table 10), meaning that first-order features potentially improve effectiveness.

5 DISCUSSION

The links between recommendation and information retrieval have also been explored elsewhere [5]. This is one of the first works to link these two areas together in a practical sense under neural models.

Contrary to our results, prior works have indicated that interaction-based models tend to be better than representation-based models. This comparison may not be fully appropriate because of two reasons. Firstly, it has been proved that feed forward neural networks model low-rank relations [1], meaning that simple implicit interaction learning models can mimic the behaviour of any explicit interaction learning models. Secondly, we showed that FwFM outperforms NRM-F, meaning that different architectures have different performance. The conclusion can vary depending on the model used for the experiment. A more detailed exploration on when interaction- vs representation-based models work seems to be needed.

The models that learned query-field interactions outperformed models trained using all interactions in both NRM-F and FwFM. This may be because query-field interactions are particularly important in document ranking, and adding irrelevant feature interactions may introduce noise into the model, resulting in degraded performance.

The original implementation of NRM-F does not use first-order field interactions. This may be because feeding those features are considered to overfit the model. For example, if there is a feature that indirectly represents the item's popularity, it could appear at the top of the list regardless of the user's intent. However, recommendation models usually do not care about the case. In a sense, feeding first-order features could improve performance because machine learning models eventually update parameters to minimize the loss.

In non-linear field interactions we showed how only FwFM's performance was improved. This may be because FwFM is more robust to noisy features to some extent since FwFM has weights that decrease the impact of not important features. The result suggests that feeding non linear interactions potentially improves performance.

6 CONCLUSIONS

We have shown how non-linearities in field-to-field interactions have an impact in ranking performance, potentially improving effectiveness.

Models that learned query-field interactions outperformed models trained using all interactions. Models including selected field-to-field features did not outperform models considering query-field interactions.

Our results also suggest an important effect of the chosen neural architecture on the performance of the ranking model, regardless of the type of interactions being considered.

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TBD.

REFERENCES

- [1] Alex Beutel, Paul Covington, Sagar Jain, Can Xu, Jia Li, Vince Gatto, and Ed H Chi. 2018. Latent cross: Making use of context in recurrent recommender systems. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*. 46–54.
- [2] Christopher J Burges, Robert Ragno, and Quoc V Le. 2007. Learning to rank with nonsmooth cost functions. In *Advances in neural information processing systems*. 193–200.
- [3] Mostafa Dehghani, Hamed Zamani, Aliaksei Severyn, Jaap Kamps, and W. Bruce Croft. 2017. Neural Ranking Models with Weak Supervision. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval* (Shinjuku, Tokyo, Japan) (SIGIR '17). Association for Computing Machinery, New York, NY, USA, 65–74. <https://doi.org/10.1145/3077136.3080832>
- [4] Po-Sen Huang, Xiaodong He, Jianfeng Gao, Li Deng, Alex Acero, and Larry Heck. 2013. Learning deep structured semantic models for web search using clickthrough data. In *Proceedings of the 22nd ACM international conference on Information & Knowledge Management*. ACM, 2333–2338.
- [5] Surya Kallumadi, Bhaskar Mitra, and Tereza Iofciu. 2018. A Line in the Sand: Recommendation or Ad-Hoc Retrieval? Overview of RecSys Challenge 2018 Submission by Team BachPropagate. In *Proceedings of the ACM Recommender Systems Challenge 2018* (Vancouver, BC, Canada) (RecSys Challenge '18). Association for Computing Machinery, New York, NY, USA, Article 7, 6 pages. <https://doi.org/10.1145/3267471.3267478>
- [6] Jinyoung Kim, Xiaobing Xue, and W. Bruce Croft. 2009. A Probabilistic Retrieval Model for Semistructured Data. In *Advances in Information Retrieval*, Mohand Boughanem, Catherine Berrut, Josiane Mothe, and Chantal Soule-Dupuy (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 228–239.
- [7] Jin Young Kim and W Bruce Croft. 2012. A field relevance model for structured document retrieval. In *European Conference on Information Retrieval*. Springer, 97–108.
- [8] Binsheng Liu, Xiaolu Lu, Oren Kurland, and J. Shane Culpepper. 2018. Improving Search Effectiveness with Field-Based Relevance Modeling. In *Proceedings of the 23rd Australasian Document Computing Symposium* (Dunedin, New Zealand) (ADCS '18). Association for Computing Machinery, New York, NY, USA, Article 11, 4 pages. <https://doi.org/10.1145/3291992.3292005>
- [9] B. Mitra and N. Craswell. 2018. . <https://doi.org/10.1561/15000000061>
- [10] Bhaskar Mitra, Corby Rosset, David Hawking, Nick Craswell, Fernando Diaz, and Emine Yilmaz. 2019. Incorporating query term independence assumption for efficient retrieval and ranking using deep neural networks. *arXiv preprint arXiv:1907.03693* (2019).
- [11] Priyanka Nigam, Yiwei Song, Vijai Mohan, Vihan Lakshman, Weitain Ding, Ankit Shingavi, Choon Hui Teo, Hao Gu, and Bing Yin. 2019. Semantic Product Search. *CoRR abs/1907.00937* (2019). [arXiv:1907.00937](http://arxiv.org/abs/1907.00937)
- [12] Paul Ogilvie and Jamie Callan. 2003. Combining Document Representations for Known-Item Search. In *Proceedings of the 26th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval* (Toronto, Canada) (SIGIR '03). Association for Computing Machinery, New York, NY, USA, 143–150. <https://doi.org/10.1145/860435.860463>
- [13] Junwei Pan, Jian Xu, Alfonso Lobos Ruiz, Wenliang Zhao, Shengjun Pan, Yu Sun, and Quan Lu. 2018. Field-weighted factorization machines for click-through rate prediction in display advertising. In *Proceedings of the 2018 World Wide Web Conference*. 1349–1357.
- [14] Benjamin Piwowarski and Patrick Gallinari. 2003. A machine learning model for information retrieval with structured documents. In *International Workshop on Machine Learning and Data Mining in Pattern Recognition*. Springer, 425–438.
- [15] Stephen Robertson, S. Walker, S. Jones, M. M. Hancock-Beaulieu, and M. Gatford. 1995. Okapi at TREC-3. In *Overview of the Third Text REtrieval Conference (TREC-3)* (overview of the third text retrieval conference (trec-3) ed.). Gaithersburg, MD: NIST, 109–126. <https://www.microsoft.com/en-us/research/publication/okapi-at-trec-3/>
- [16] Stephen Robertson, Hugo Zaragoza, and Michael Taylor. 2004. Simple BM25 Extension to Multiple Weighted Fields. In *Proceedings of the Thirteenth ACM International Conference on Information and Knowledge Management* (Washington, D.C., USA) (CIKM '04). Association for Computing Machinery, New York, NY, USA, 42–49. <https://doi.org/10.1145/1031171.1031181>
- [17] Fatemeh Sarvi, Nikos Voskarides, Lois Mooiman, Sebastian Schelter, and Maarten de Rijke. 2020. A Comparison of Supervised Learning to Match Methods for Product Search. *arXiv preprint arXiv:2007.10296* (2020).
- [18] Krysta M Svore and Christopher JC Burges. 2009. A machine learning approach for improved BM25 retrieval. In *Proceedings of the 18th ACM conference on Information and knowledge management*. 1811–1814.
- [19] Ross Wilkinson. 1994. Effective retrieval of structured documents. In *SIGIR '94*. Springer, 311–317.
- [20] Hamed Zamani, Bhaskar Mitra, Xia Song, Nick Craswell, and Saurabh Tiwary. 2017. Neural Ranking Models with Multiple Document Fields. *CoRR*

abs/1711.09174 (2017). arXiv:1711.09174 <http://arxiv.org/abs/1711.09174>